

Expanding SPoRT RGBs and Machine Learning Techniques to Enhance Air Quality Monitoring in Southern Asia

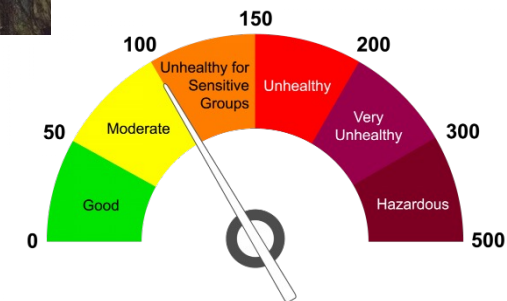
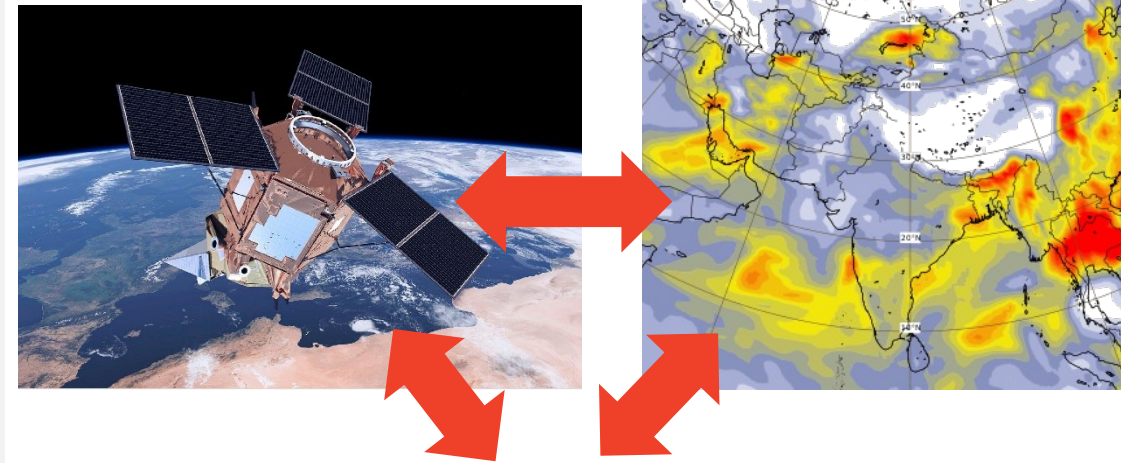
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Andrew T. White³, Kevin K. Fuell³, Connor H. Welch^{**3}

¹ENSCO, Inc.

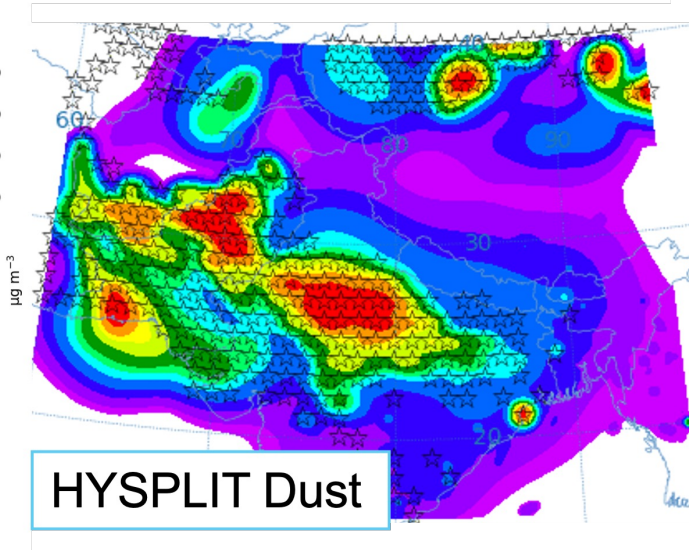
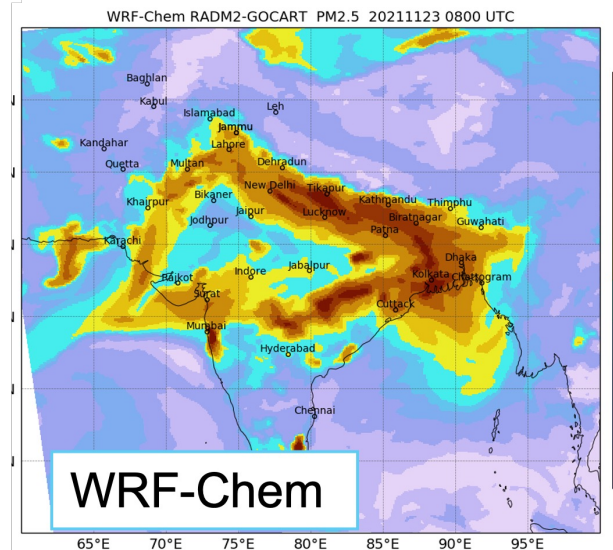
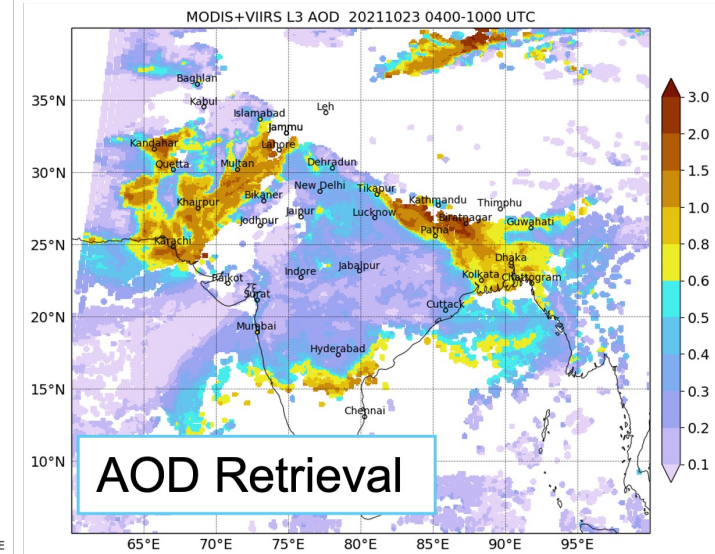
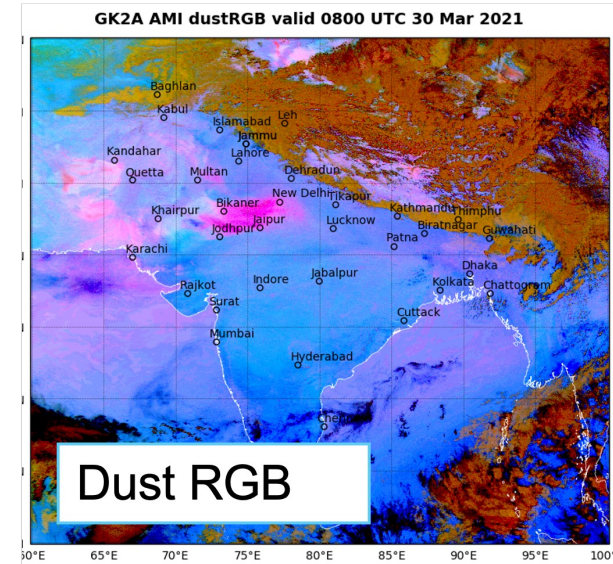
²NASA Short-term Prediction Research and Transition Center

³The University of Alabama in Huntsville

- Air pollution is a serious threat to human health
- Poor air quality common to region
- Difficult to monitor and predict due to strong / rapidly evolving emissions
- New generation satellite sensors can advance monitoring capabilities
- Ground-based sensors complement satellite & validate model data

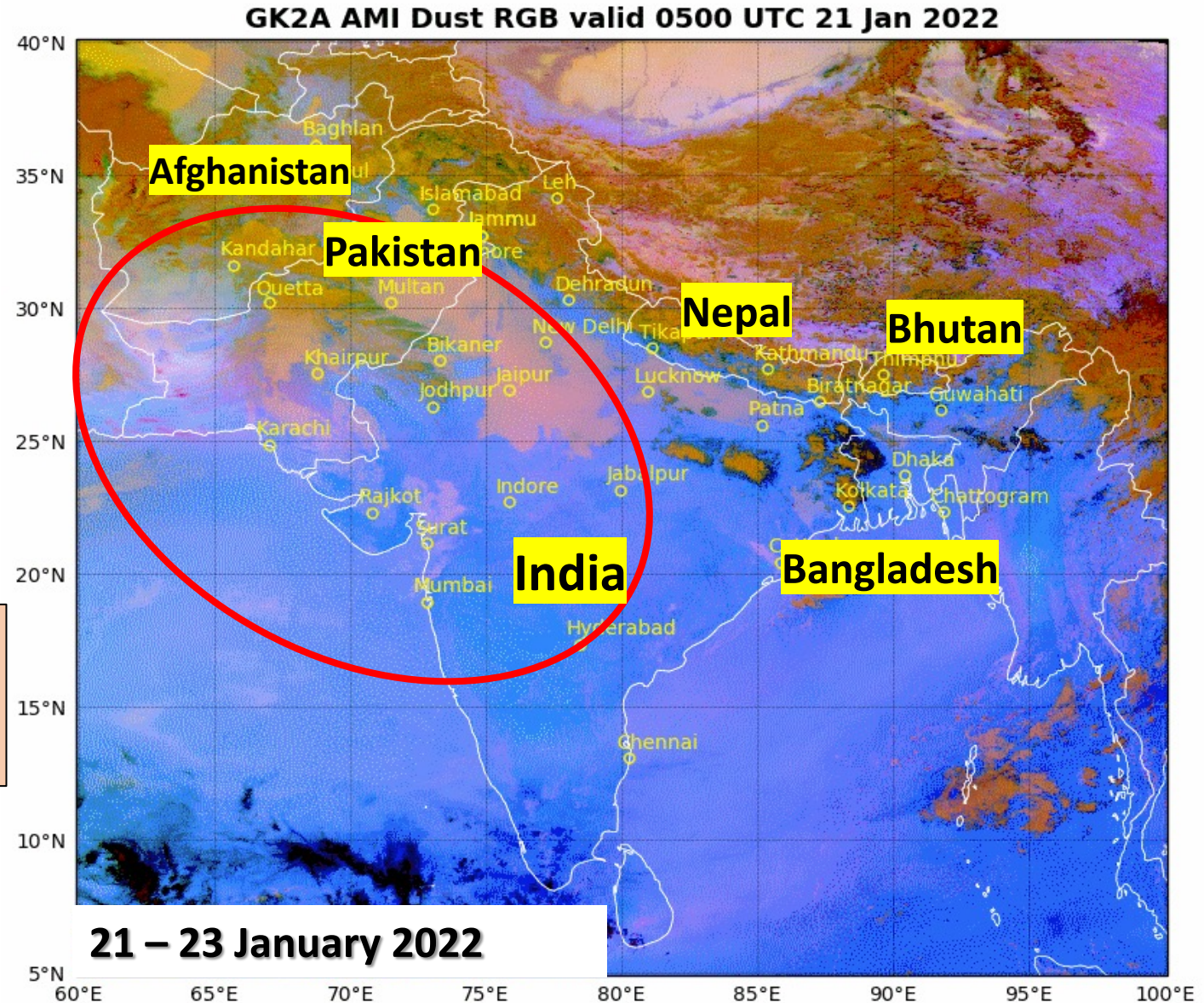


- Red-Green-Blue (RGB) satellite products for monitoring dust, fog, fires, and smoke
- Trace gas / aerosol products to track pollution at surface and aloft
- Chemical transport model for predicting air quality and providing timely warnings
- Dispersion model for predicting dust concentrations & enabling rapid response to dust storms



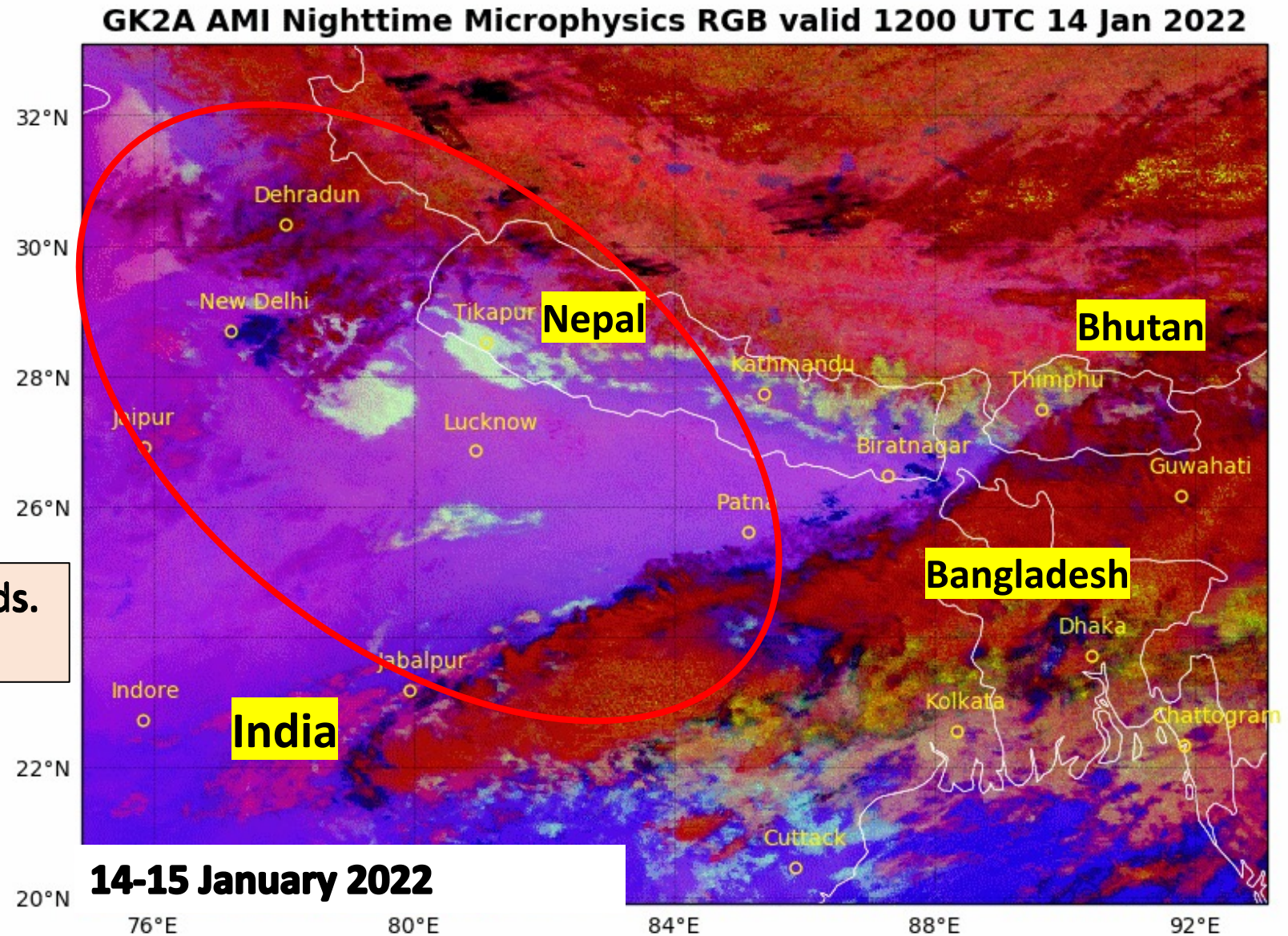
Satellite Product
○ Dust RGB
Application
○ Dust Plume Monitoring

Dust areas denoted by magenta shading (24-h coverage)



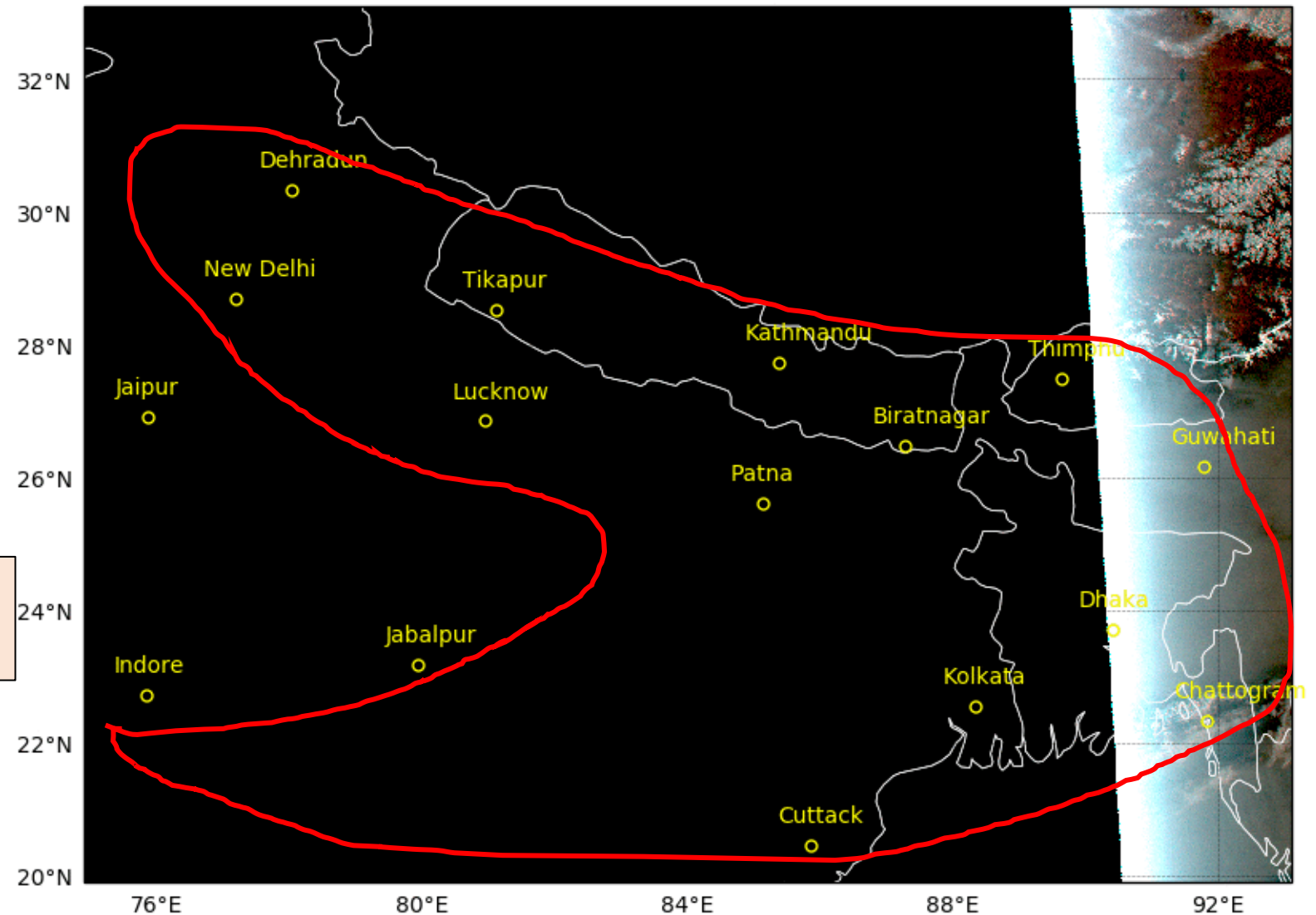
Satellite Product
○ Nighttime Microphysics RGB
Application
○ Fog, smog, & low-cloud detection

Highlights fog & low clouds.
(Limitation: night-only)



Satellite Product
○ Truecolor RGB
Application
○ Land surface, clouds and smoke

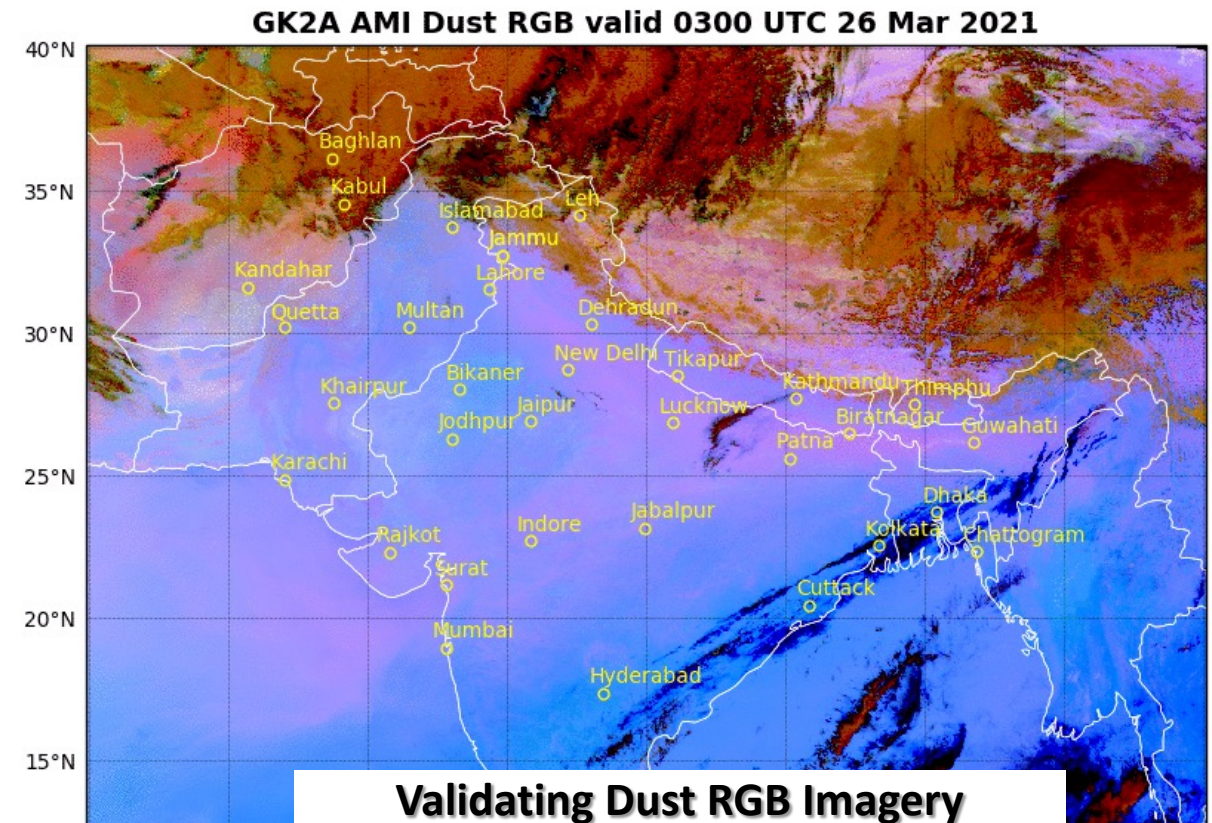
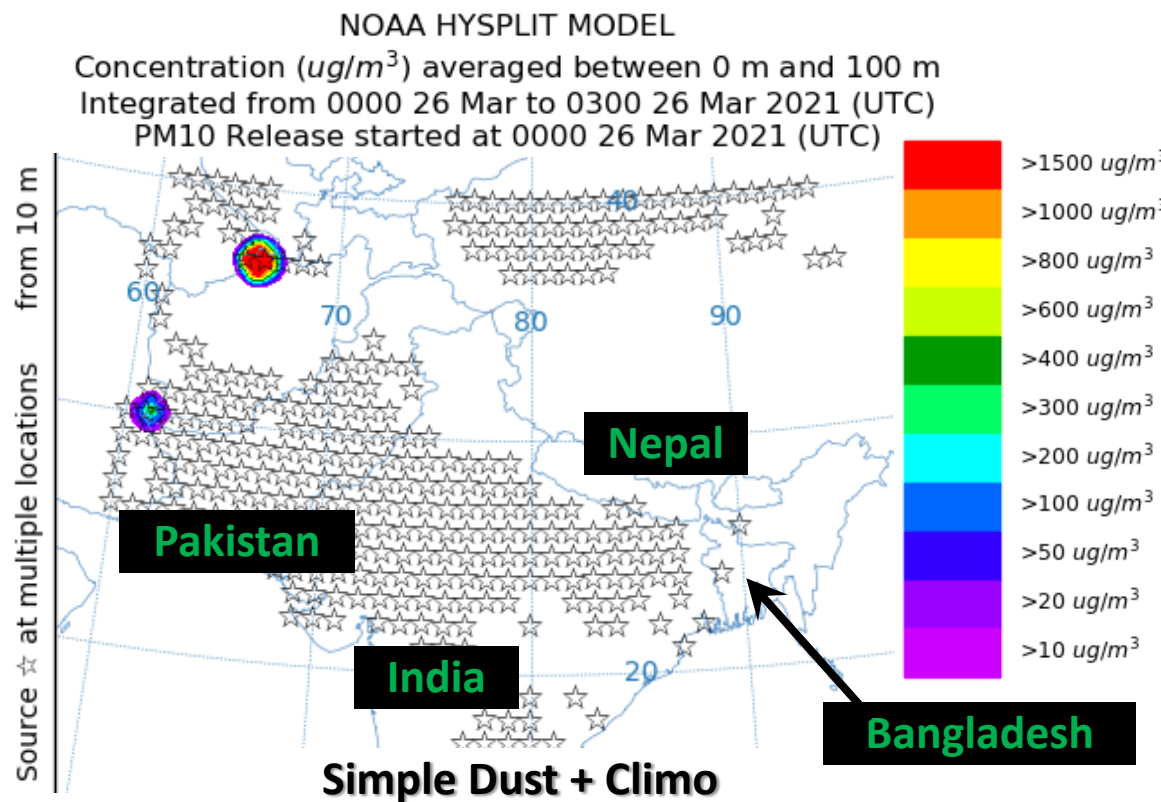
GK2A AMI Truecolor RGB valid 0000 UTC 27 Mar 2021

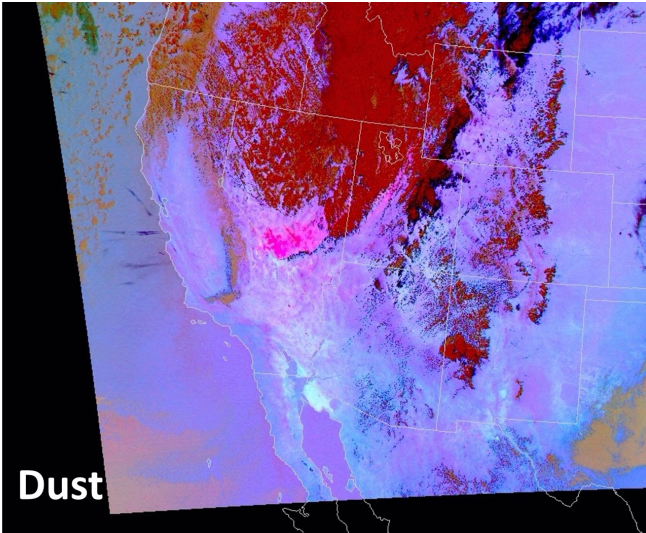


Truecolor shows regional smoke from biomass burning. (day only)

27 March 2021 Fire and smoke

- 26-31 March 2021 dust event
 - HYSPLIT simple dust algorithm with monthly satellite emission climatology
 - Room for improvement:
 - ✓ Emission climatology from 2010 study (Draxler et al. 2010; *J. Geophys. Res.*)
 - ✓ Does not account for Land-use/Land-cover changes and/or seasonal anomalies





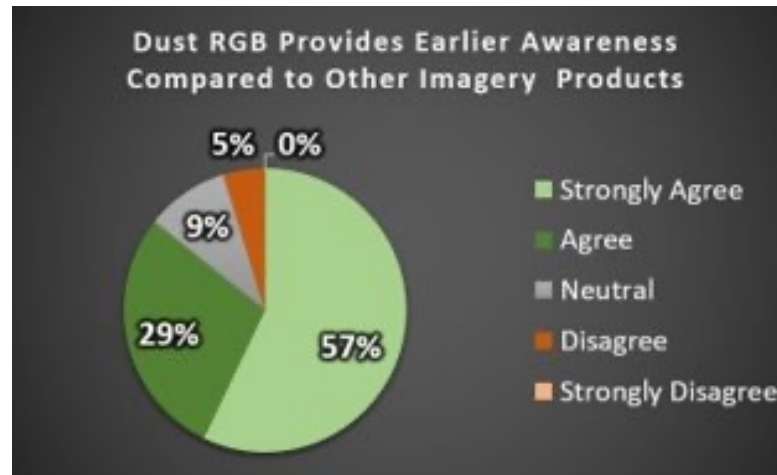
Early application & training
of MODIS/ VIIRS RGBs to
prepare for GOES-R

Early assessment of
GOES-16 Dust RGB in
operations

Limitations:

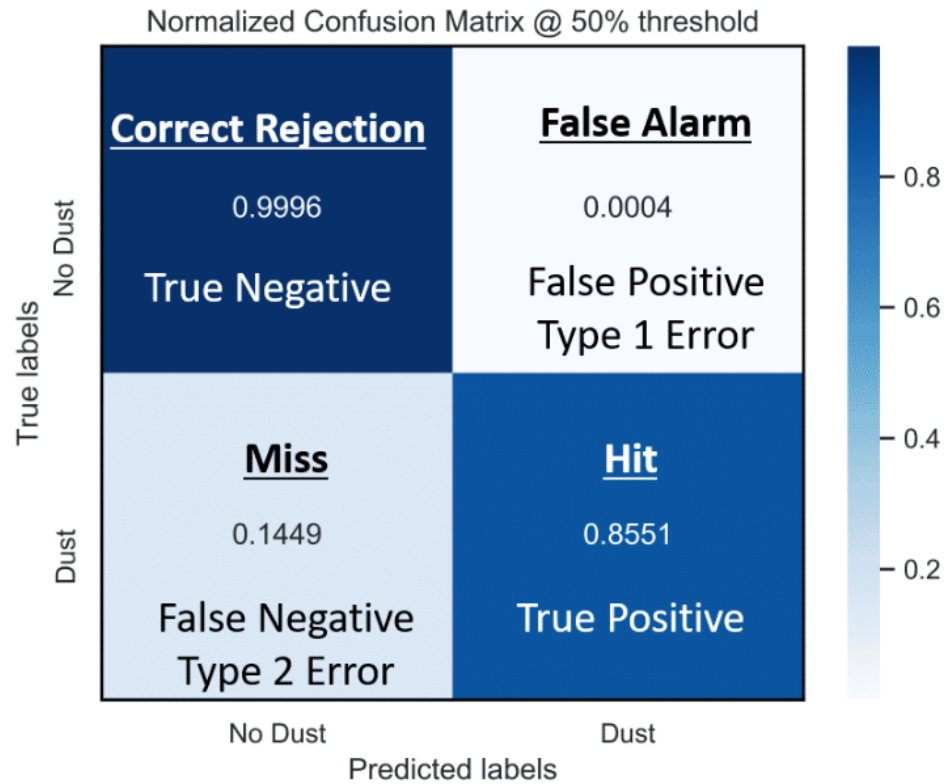
- Thin or dispersed dust
- Tracking long events into the night

Use ML/AI
to improve
detection and
interpretation



86% of Forecasters agree the
Dust RGB provided earlier
awareness of dust

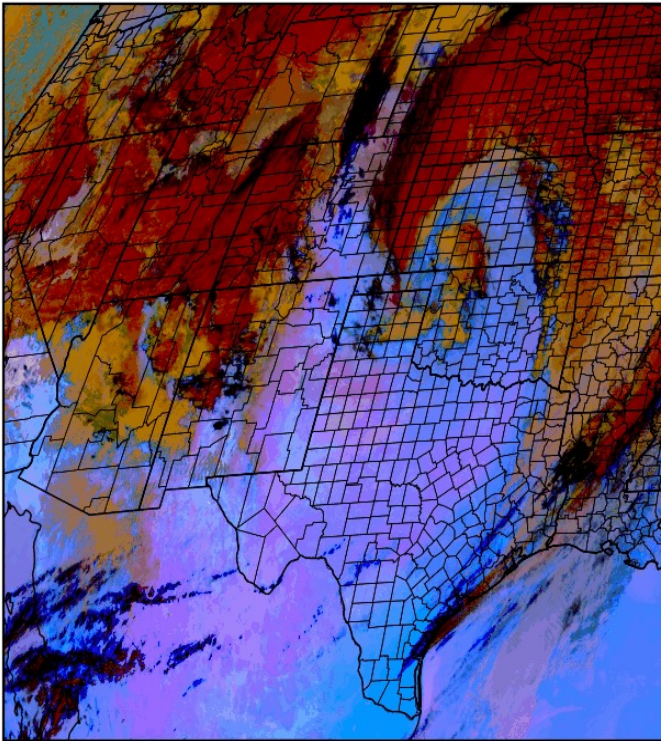
Finding Dust at Night



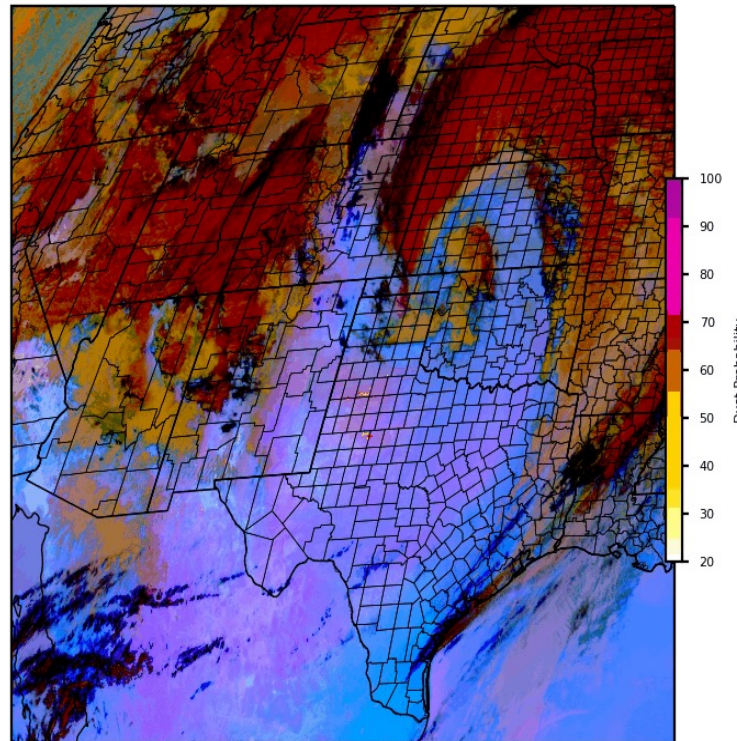
**Highly efficient at true 'dust' and 'no dust' classifications

- **DustTracker-AI** has been developed as a Day/Night model to identify dust in complex night-time scenes and increase situational awareness
- End-User Assessment & Feedback on favorable and unfavorable cases will help expand the training database and improve the model

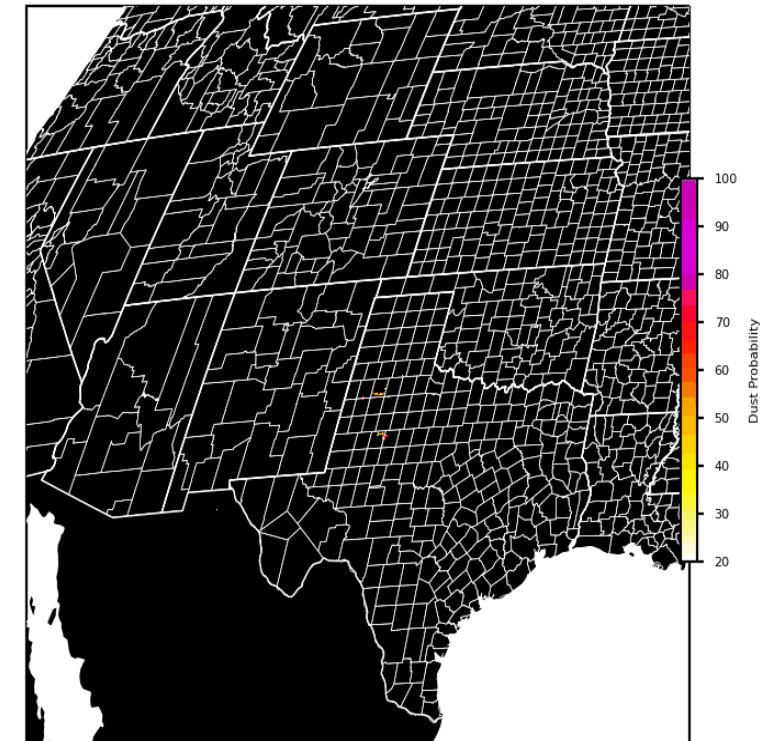
GOES-16 ABI Dust RGB 2023-02-14 17:51 UTC



GOES-16 ABI Dust RGB / Dust Probabilities 2023-02-14 17:51 UTC

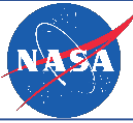


Random Forest Dust Probabilities 2023-02-14 17:51UTC



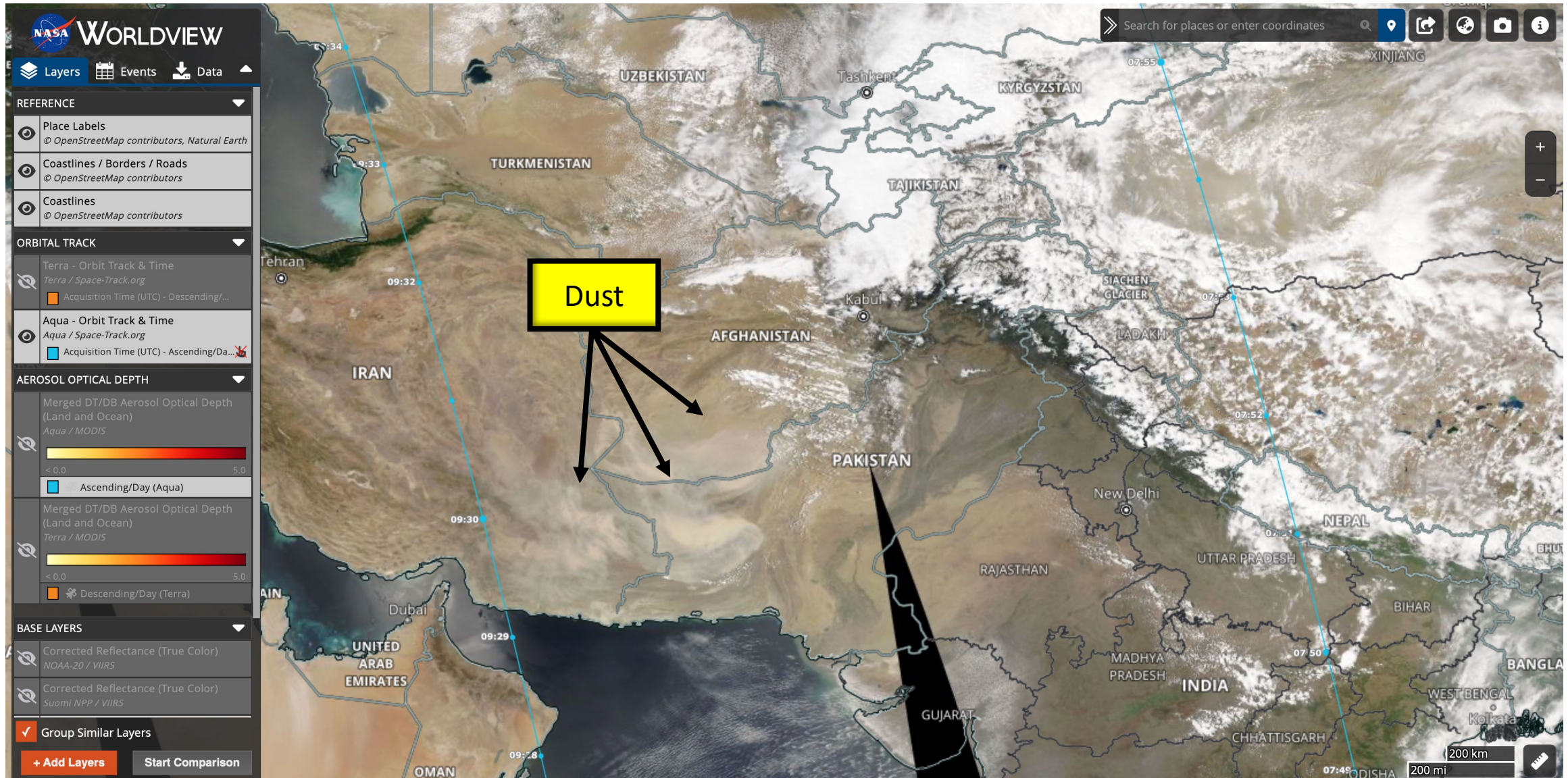
Extend AI Models to Initialize Dust and Smoke Forecasts

- Develop AI models for dust and smoke identification over south Asia
 - **Dust**: Apply U.S. random forest model and train over south Asia
 - **Smoke**: Develop new AI model over south Asia (random forest? Deep learning?)
 - Could be more challenging! Satellite smoke ID a bigger challenge over region
 - Biomass burning: small but numerous; sub-pixel size (satellite ~1-2 km)
- Currently creating training data over south Asia for both phenomena
- Use AI Tracking models to inform dispersion models
 - Early hours of identification for emission source locations
 - Initialize dispersion model (i.e., HYSPLIT) with emission locations
 - Calibrate dispersion model parameters through validation against in situ and satellite observations



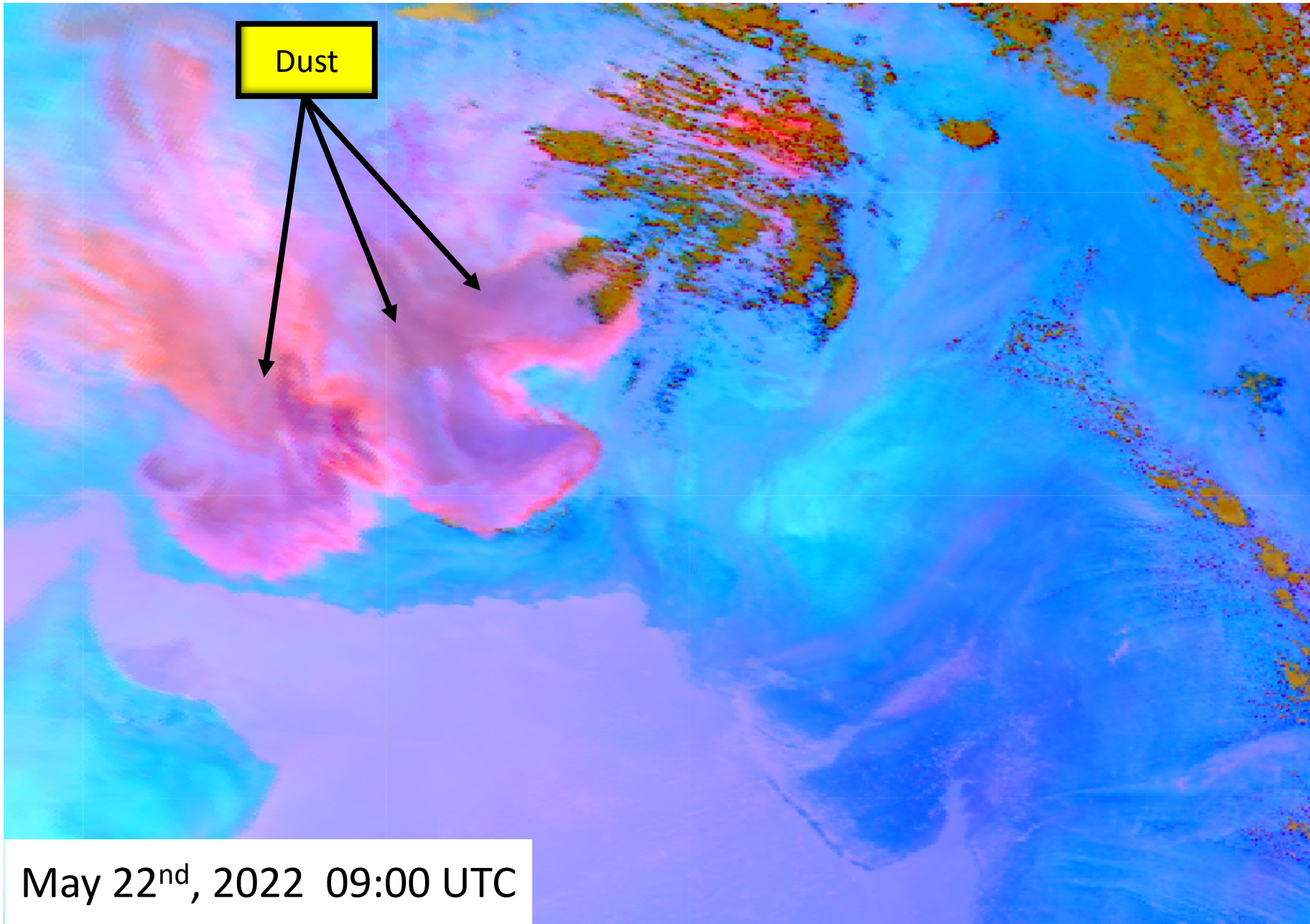
Example Training Data – Dust, Truecolor Aqua

May 22nd, 2022 09:30 UTC



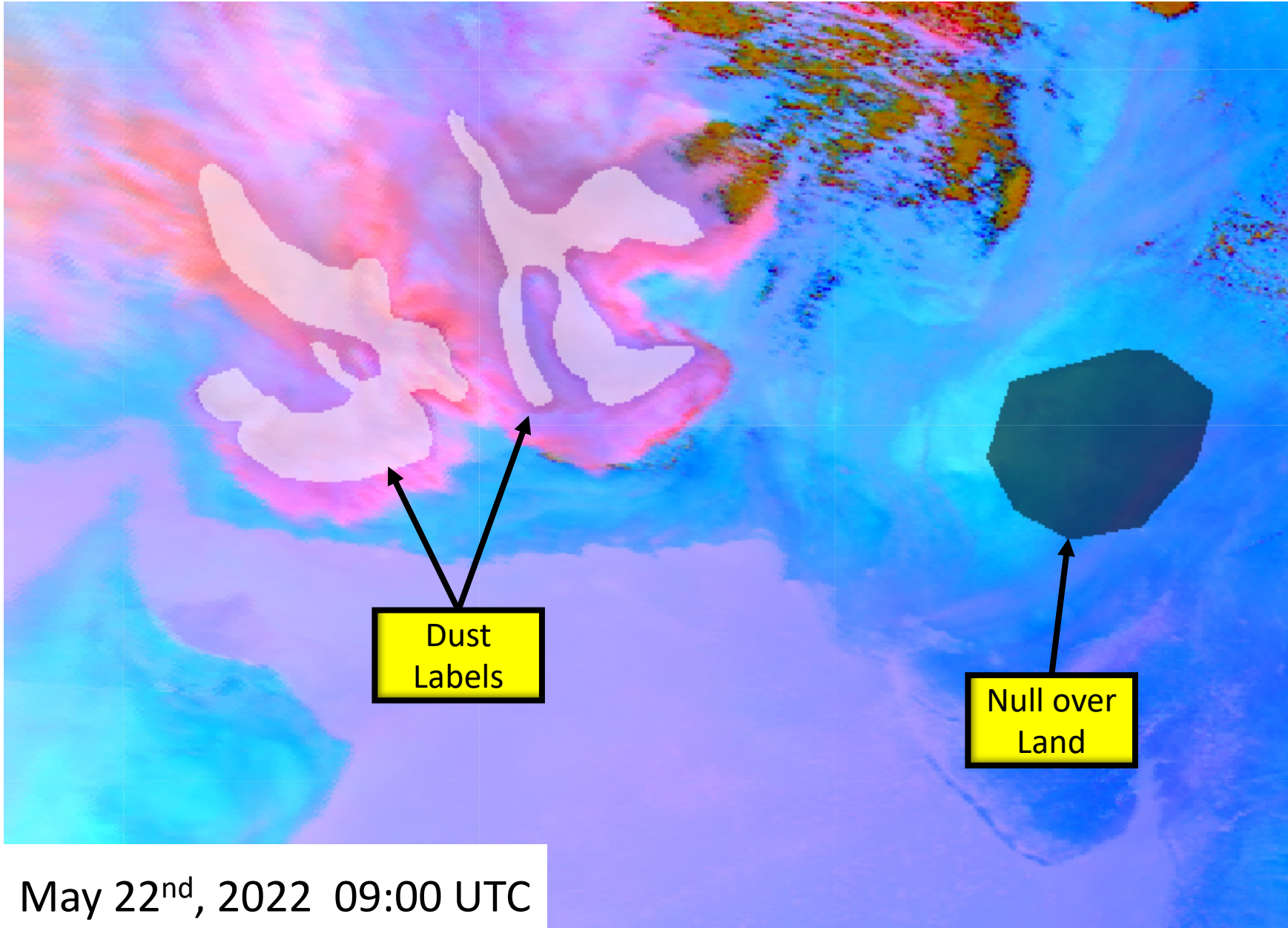


Example Training Data – Dust RGB



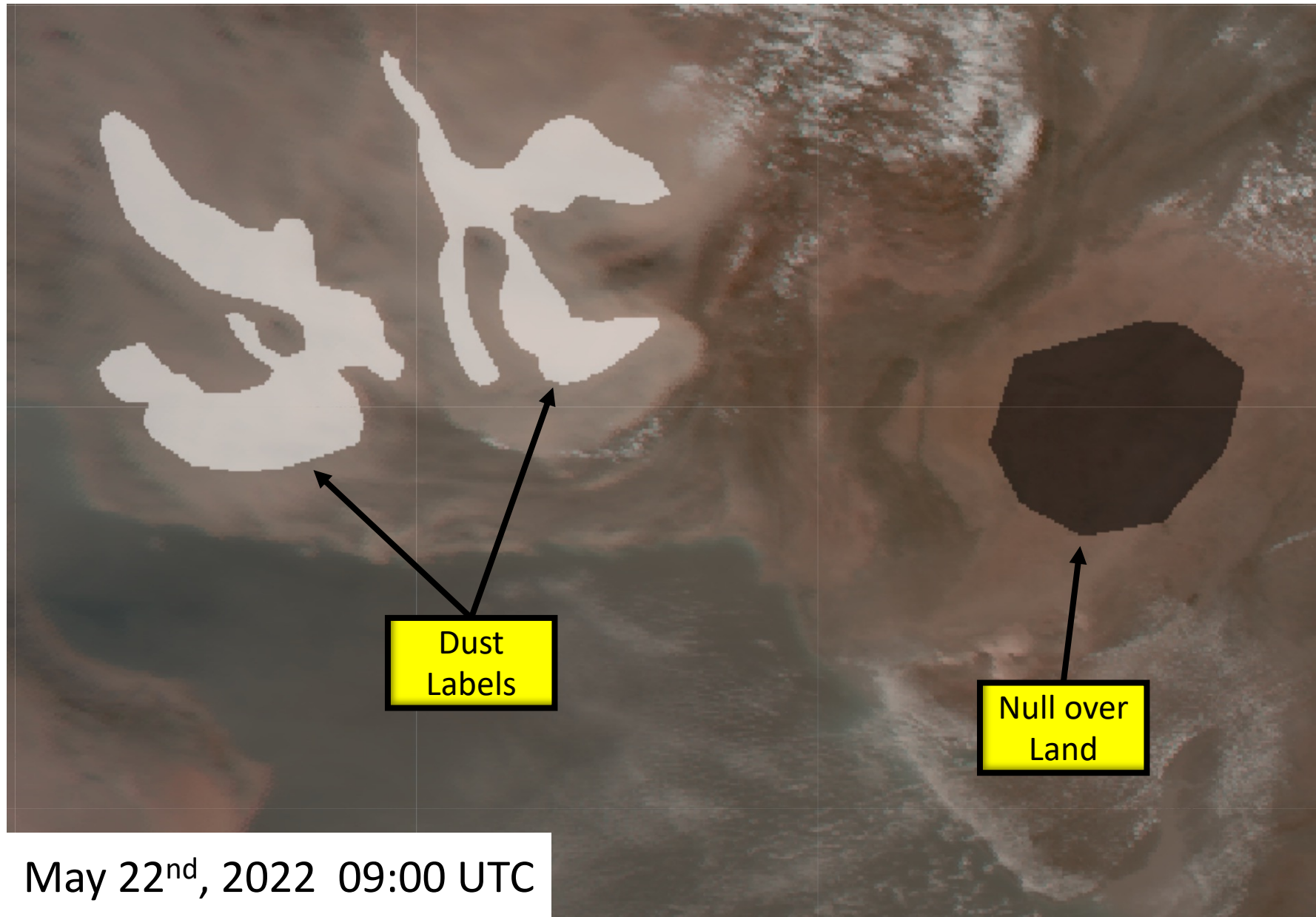


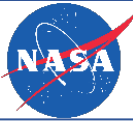
Example Training Data – Dust RGB Labeled





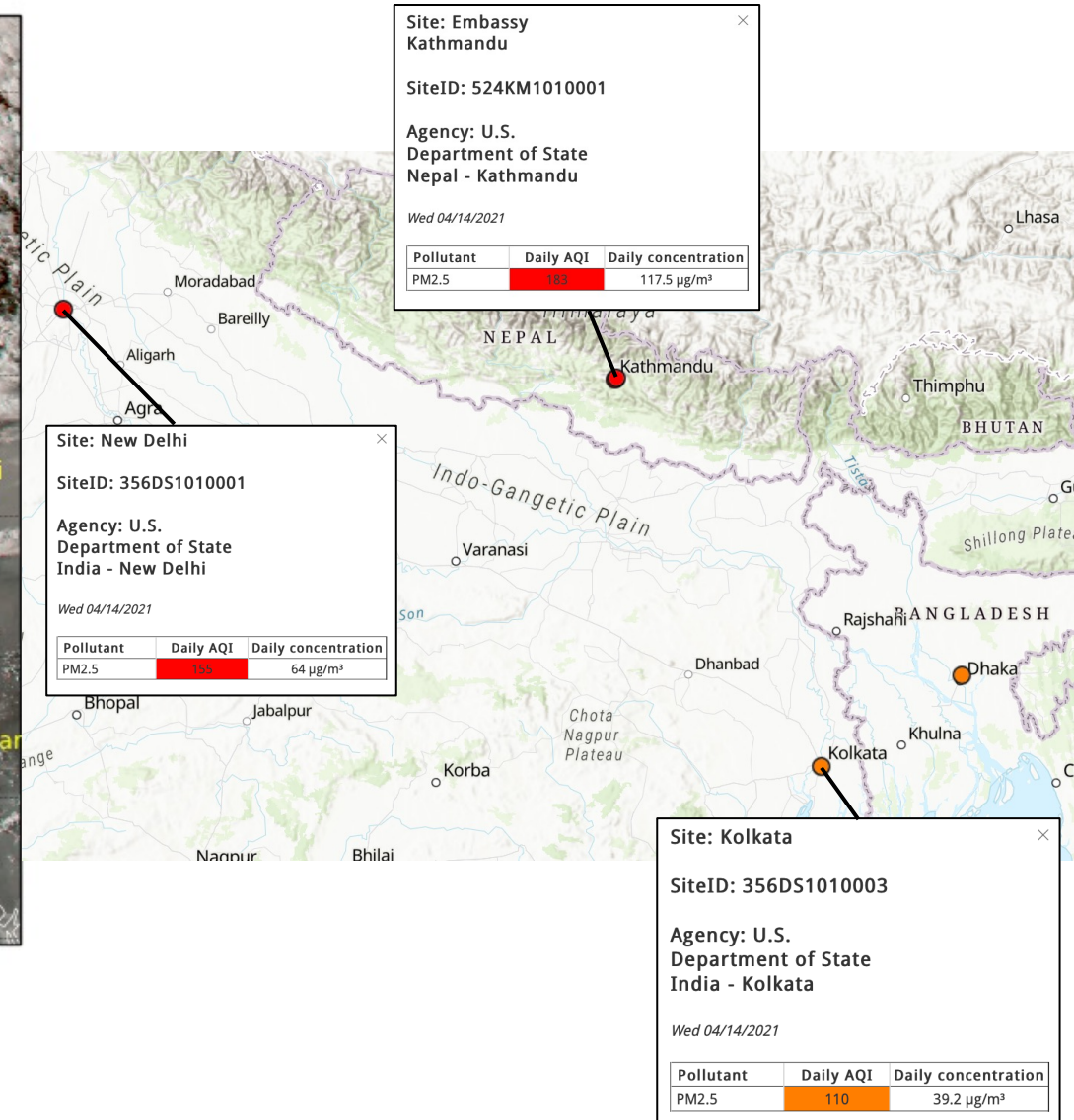
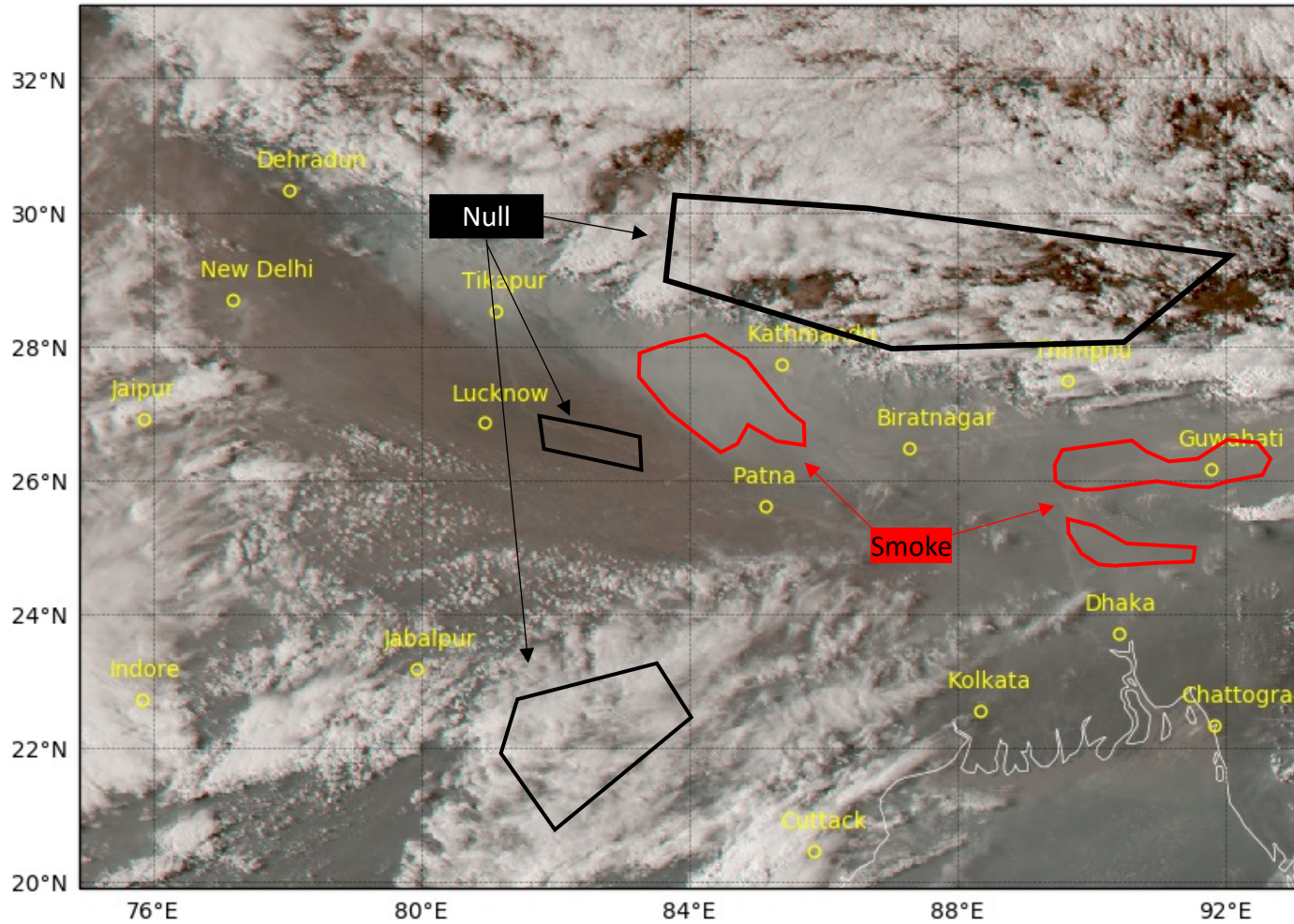
Example Training Data – True Color RGB Labeled





Example Training Data – Smoke Labeled (True Color)

GK2A AMI Truecolor RGB valid 1000 UTC 14 Apr 2021



References

Finding Dust at Night Visualization: <https://svs.gsfc.nasa.gov/5040/>

Scientific Publication: (Berndt et al. 2021)

<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021EA001788>

Real-time DustTracker-AI product:

https://weather.ndc.nasa.gov/sport/viewer/?dataset=goeseastdustmodel&product=dust_prob

NASA Earthdata Feature Article: <https://www.earthdata.nasa.gov/learn/articles/dust-m1>

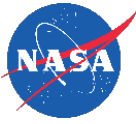
SPoRT Twitter Posts:

https://twitter.com/NASA_SPoRT/status/1630668959883096067

https://twitter.com/NASA_SPoRT/status/1648348153991634945

https://twitter.com/NASA_SPoRT/status/1631457114605379587

https://twitter.com/NASA_SPoRT/status/1630668959883096067



Dust ML Paper
(Berndt et al. 2021)

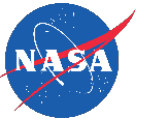


HKH Project Webpage



NASA Visualization Studio
Finding Dust at Night





Backup Content (for Q&A)

$$Red = \left(\frac{R - R_{min}}{R_{max} - R_{min}} \right)^{1/\gamma}$$

$$Green = \left(\frac{G - G_{min}}{G_{max} - G_{min}} \right)^{1/\gamma}$$

$$Blue = \left(\frac{B - B_{min}}{B_{max} - B_{min}} \right)^{1/\gamma}$$

Where:

- R , G , or B is the present pixel value brightness temperature
- min and max are the calibrated thresholds applied to a given channel or channel difference
- $1/\gamma$ is the calibrated power scale to affect the color stretching

<i>Satellite Product</i>	<i>Red</i>	<i>Green</i>	<i>Blue</i>	<i>Gamma</i>	<i>Applications</i>
Dust RGB	IR _{12.3} – IR _{10.5} (-6.7 to +2.6°C)	IR _{11.2} – IR _{8.7} (-0.5 to +20°C)	IR _{10.5} (-11.95 to +15.55°C)	1.0 (RB) 2.5 (G)	Dust plume monitoring
Nighttime Microphysics (night only)	IR _{12.3} – IR _{10.5} (-6.7 to +2.6°C)	IR _{10.5} – SW _{3.8} (-3.1 to +5.2°C)	IR _{10.5} (-29.55 to +19.45°C)	1.0	Fog, smog, and low-cloud detection
Truecolor RGB (day only)	VIS _{0.64} (0 to 1.0 refl)	VIS _{0.51} (0 to 1.0 refl)	VIS _{0.47} (0 to 1.0 refl)	2.2	Land surface, clouds and smoke
Natural Color Fire RGB (day only)	SW _{3.8} (0 to 60°C)	VIS _{0.87} (0 to 1.0 refl)	VIS _{0.64} (0 to 1.0 refl)	0.4 (R) 1.0 (GB)	Fire hot spots [and smoke]
Fire hot spot detection (GEO + LEO)	AMI channels combined with land type, sfc temp, and MODIS/VIIRS to identify fire locations at hourly frequency				Fires; early warning on smoke hazards
Hourly Composite AOD	Uses suite of AMI VIS and IR channels to provide high-quality depiction of total-columnar atmospheric aerosols				air pollution / data assimilation
Hourly Composite PM_{2.5}	Surface PM _{2.5} derived from hourly AOD and WRF-Chem with data assimilation model output				Air quality and health

- Overcoming the limitations of night-time dust detection is addressed by using expert analysis and remote sensing principles to develop training data, model inputs, and architecture.

Focus on refining the training for nocturnal dust detection

- Collect night-time training dataset
- Classify false surface and smoke detections

- GOES-16 ABI imagery in the SW U.S. Jan. 2018 - Jun. 2020
- Cases were randomly split for Dust ML model training (60%), testing (20%), and validation (20%)
- A total of 28 cases were gathered, which incorporates 83 distinct images a total of 790,921 dust pixels and 37,698,467 null pixels

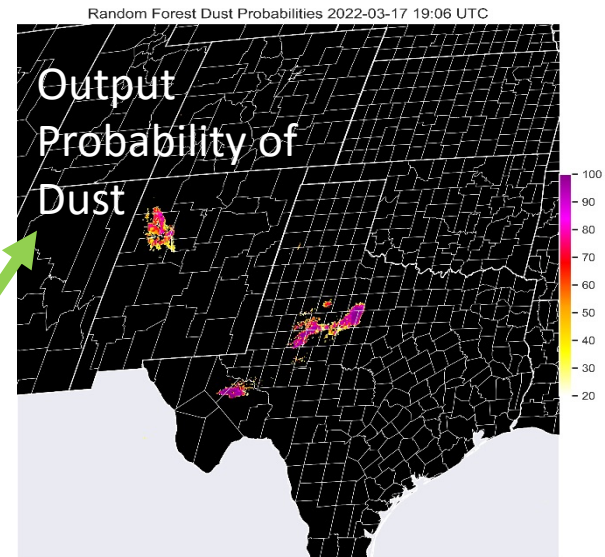
Model Inputs

Single channels: 7.3, 10.35, 11.2, 12.3, 13.3

Differences: 12.3-10.35
11.2-8.4

Dust RGB components

Random Forest Model



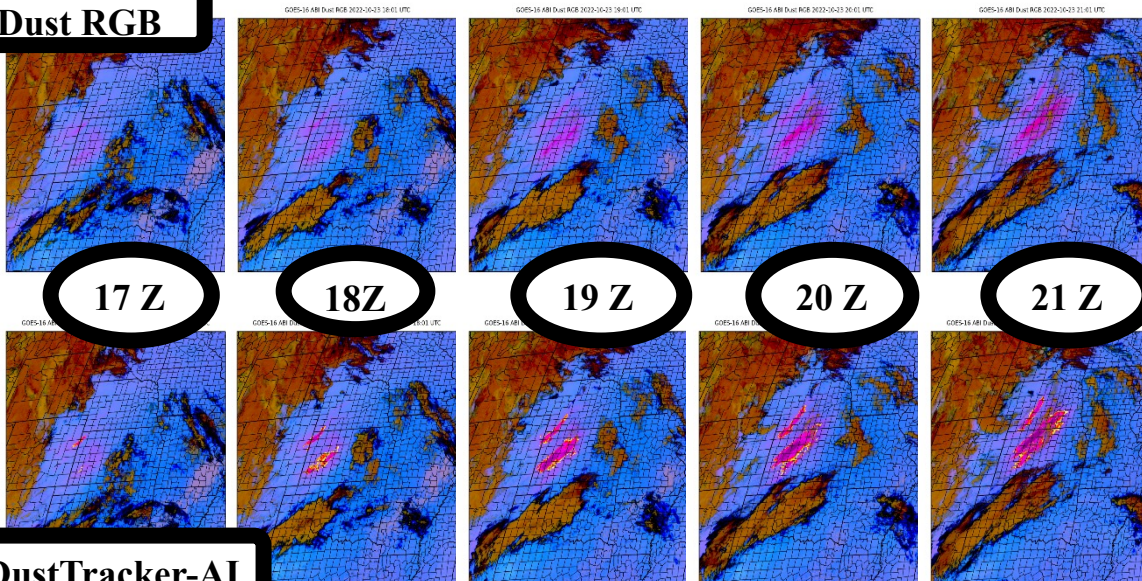
Evaluate Training, Model Inputs, & Performance w/ Stat Approaches

- Loss functions/Jaccard score
- Confusion matrix
- Permutation Importance
- ROC/AUC
- Plus a few more

- Total of 39 training Day & Night cases were gathered,
 - Incorporates 115 distinct images
 - Total of **1,154,064 dust** pixels and **256,932,301 null** pixels
- Assessed the incorporation of visible channels

Daytime Case

Dust RGB



DustTracker-AI

Night-time Case

